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Towards a Knowledge-Based Control of a Complex Industrial Process

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1 Introduction

Difficulty to ensure optimal settings of all adjustable parameters is dominant problem for complex and fast industrial processes such as cold rolling. The modern cold rolling mill is controlled by a distributed control system consisting of many nodes of several types such as regulators, controllers, data acquisition nodes, database servers and operator consoles. Proper tuning of all single controllers is pre-requisite. However, the quality of the product still depends on operator's skills and experience because of big amount of many possible working modes and adjustments of the machine.

For most cases the product quality criteria lay within the admissible range. Nevertheless there always exist reserves to improve quality. The importance of that increases with a long-termed production.

The networked control system provides a lot of process data in which at least some reasons of quality variations are hidden. A consortium consisting of people from university, academia and industry has been created to cope this problem using probabilistic data clustering. The idea is to develop a decision support tool that will provide advice for operators to help them in keeping adjustable mill parameters close to optimal settings.

2 Rolling mill control

In principle the basic control of a reversing cold rolling mill can be divided into two parts: control of the roll-positioning system (screw-down) and electrical regulation of the main mill drive(s) and drives of coilers/decoilers. The second problem is nowadays being solved mostly by configuration and coordination of a set of more or less sophisticated, ready-to-market devices. On the other hand, the first problem includes several specific tasks the solutions of those slightly differs from producer to producer.

Well tuned basic level of control is needed for a proper function of controllers of strip thickness, strip profile (flatness) and/or elimination of roll eccentricity [1].

2.1 Roll-positioning system

The most important task of the roll-positioning system is to follow the position set-points given by operators and/or thickness and profile controllers. For this purpose the system is equipped with a pair of high-speed hydraulic actuators (one for each side of the mill). These are governed by digital controllers basically of a PI structure with a variable gain ensuring an identical speed of movement for both sides.

2.2 Thickness controller

Conditions of rolling are changing because of various types of processed material and different settings of the machine according to pass schedules. Variations of many technological values from which only some are directly measurable also influence given process. For these reasons, a proven model-based adaptive thickness controller is being used.

Parameters of the process model are considered to be apriori unknown and time-varying. Their on-line estimation is based on a least-squares algorithm with a selective exponential forgetting of older values. Estimated values are used for evaluation of control coefficients.

3 Analysis of process data

Typically hundreds of signals are available within the rolling mill control system including analog, digital (incremental) and logical values. Among them about forty

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signals are somehow relevant from the problem point of view. As some of these values are correlated twelve data signals were selected for final evaluation. For technical reasons, majority of the first phase of experiments on real data were carried out with three or four most important signals [2]. Similarly, the preliminary versions of developed algorithms were tested on data simulated by the very simplified model of the process.

3.1 Quality criteria

The coils produced by the rolling mill mostly satisfy the quality requirements given both by current customers and appropriate standards. However, the product quality varies slightly in an unpredictable way. The aim of research reported is to find some statistically important relationship between the product quality and process parameters settings.

The variation of the output thickness H_2 is one of the main quality measures of the processed metal strips. Several quality criteria are recognized:

1. Statistical coefficient C_p defined as:

$$C_p = \frac{tol^+_{h_2} + |tol^-_{h_2}|}{6\,\sigma_{H_2}}\,, \tag{1}$$

   where H_2 denotes output thickness, h_2 is its deviation from the nominal value H_{2nom},

   $tol^+_{h_2}$, $tol^-_{h_2}$ are boundaries of tolerance range of h_2 and

   $\bar{H}_2$, σ_{H_2} are mean and standard deviation of the output thickness H_2 respectively.

2. Statistical coefficient C_{pk} defined as:

$$C_{pk} = \frac{\min(\bar{h}_2 - tol^-_{h_2},\; tol^+_{h_2} - \bar{h}_2)}{3\,\sigma_{H_2}}\,, \tag{2}$$

   where $\bar{h}_2$ denotes mean of h_2.

3. Coefficient C_{per} representing the percentage of the output thickness deviation h_2 being within the tolerance range $\langle tol^-_{h_2},\, tol^+_{h_2}\rangle$.

The aim of the quality control is to optimize coefficients C_p, C_{pk}, C_{per}.

3.2 Multidimensional data clustering

Consider multidimensional space with orthogonal axes where each axis corresponds to one data signal. Measured data samples create points in such space. It is reasonable to assume that several areas with a higher point density can be distinguished. These clusters of points reflect different "modes" of system behaviour depending significantly on operators.

During the analysis of process data a subtask concerning the product quality has emerged: four shifts A,B,C,D of operators alternate on the rolling mill. After each month a table is being created ordering the operator shifts according to average achieved product quality for the given sort of material.

Shift	N_C	$\bar{H}_2$ [μm]	C_p	C_{pk}	C_{per} [%]
A	82	679.7	1.89	1.85	98.95
C	98	728.1	1.85	1.82	99.49
B	118	692.4	1.69	1.66	99.08
D	100	671.0	1.59	1.52	98.35

Table 1: Quality table for four shifts of operators (N_C denotes number of coils, $\bar{H}_2$ the average output thickness and C_p, C_{pk}, C_{per} are statistical coefficients)

For one group of similar materials a correlation was found between the order of shifts and shapes of data point clusters. The table 1 shows results of four shifts in descending order concerning the average product quality. Four two-dimensional point graphs on the fig. 1 correspond to single shifts in the same order. The x-axis is related to the hydraulic pressure in the roll bending system while the y-axis corresponds to the strip tension on the input side of the rolling mill. The gray scale is used to distinguish various relative density of data points within the orthogonal grid.

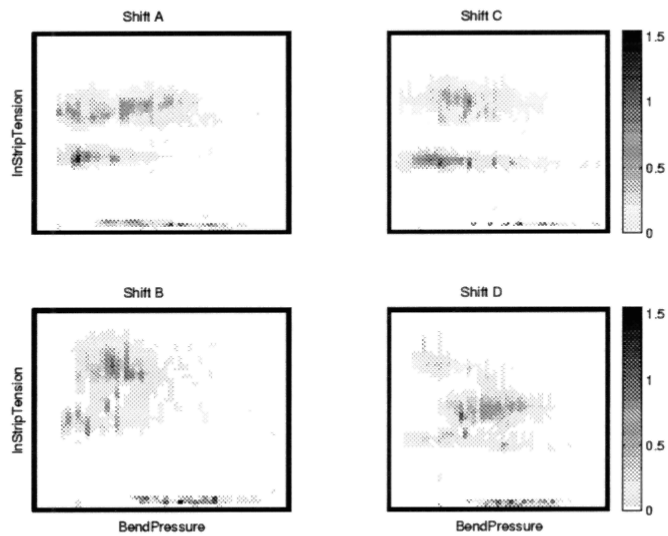

Figure 1: Relative density of data points

It can be seen that the first and second shifts succeeded to avoid settings consequenting in data located in a horizontal strip in the middle of the graph. The worst shift on the other hand used settings resulted in the probably problematic area.

It has to be emphasized that this simple correlation was not commonly found for all kinds of materials nor for every month of the production. Such a clear correlation would be at the end realized by operators or supervisors themselves. Nevertheless the example demonstrates the basic idea which is to be utilized for dimensional analysis.

The main technical problem of the approach consists in extremely huge amounts of data which are to be processed. Even in the case of limiting the processing to the most important 12 signal channels each pass of the strip produces hundreds of thousands data points which should be considered. Therefore an approach was sought to extract valuable information from these data in a suitable way.

3.3 Mixture estimation

The key task of data mining is proper choice of model describing sufficiently data occurrences. The selected data modelling has to

- be as simple as possible,
- respect high-dimensional character of data,
- allow transparent construction of advice for system operators.

Common way of data description is through localization of clusters, the multidimensional areas of high data density reflecting the most frequent system behaviour. In case of common method of cluster analysis, a significant drawback appears. The final construction of advice for operators based on clustering methods is obscure and needs a proper interpretation of results by process expert(s).

Considered mixture of probability density functions (pdf) fulfills all requirements on modelling of data occurrences. In this case, data are taken as realization (samples) from a given probabilistic distribution. Stochastic nature of this model respects possible noise and outliers. Relatively simple treatment based on conditioning and marginalization offers general way how to create and visualize a suitable advice to operators.

The mixture of weighted Gaussian probability density functions (Gaussian components) was selected among possible pdfs. Then probability of data sample is modelled by

$$p(d_t) = \sum_c \alpha_c \, \mathcal{N}(\mu_c, R_c)$$

where d_t is data vector containing values of signals measured in time instant t, $\mathcal{N}(\mu_c, R_c)$ denotes c-th Gaussian pdf determined by mean μ_c and covariance matrix R_c. $\alpha_c \geq 0, \sum_c \alpha_c = 1$ are component weights. Such model is flexible enough to model a wide class of systems. It is given by a simple parametrisation consisting of (unknown) means, covariance matrices and weights.

Problem of mixture estimation (i.e. estimation of all parameters) can be solved by Bayesian approach where combination of data and prior information is well established. A novel recursive quasi-Bayesian algorithm was introduced in [3]. Algorithm is based on sequential re-estimation of probability distribution on parameters with respect to newly measured data together with predictive capability of corresponding Gaussian component. The factorised form of sufficient statistics avoids evaluation failure caused by numerical reasons. The recursive nature of algorithm will be well appreciated especially during processing many data records as appears in case of modelled complex systems.

The proper selection of starting point is a significant problem in all the mixture estimation methods. Many different approaches and algorithms was published, e.g. [4]. Here, a probabilistic mixture estimation was combined with a method of cluster analysis, Mean-Tracking algorithm [5]. This rapid algorithm, able to handle huge amount of data samples, looks for number and centres of data clusters. The centres found serve as a rough estimate of means of Gaussian component in a probabilistic mixture.

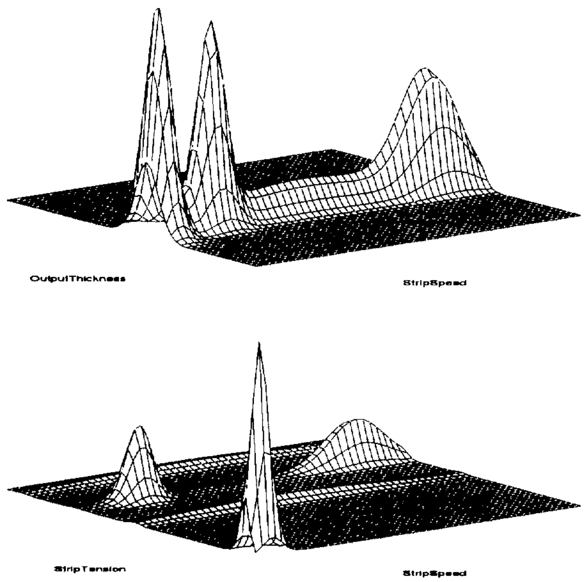

Figure 2: Results of mixture estimation; strip speed vs. output thickness (upper figure) and strip speed vs. strip tension (lower figure)

During the first phase of project, the proposed quasi-Bayesian algorithm was tested on simulated data. Five signals of relevant system variables were processed. Illustrative example of results in fig. 2 presents 2-dimensional projection of a 5-dimensional estimated mixture of pdfs. The satisfactory results as well as the advantage of the recursive nature of the algorithm support its further employment. However, the expected sensitivity on starting conditions was observed. It calls for further improvement of the initial phase and data pre-processing.

The estimated components of mixture resulting from quasi-Bayes algorithm enter to quality evaluation. The quality marker corresponding to the quality criteria is set to all estimated component. The best component (one multivariate Gaussian probability density function) serves as "guide" for operator. Note not all signals which influence quality can be tuned (e.g. input thickness) but such variables have to be involved into data processing and consequently into advice construction as well. Thus, the conditional probability distribution, derived from selected Gaussian component, is the base of the advice. The conditional probability is recalculated for each time instant in dependence on incoming signals. Then the operator is guided by a time variant recommendation reacting on changes of the system.

3.4 Visualization

An additional task is to find a suitable way how to provide the information to the rolling mill operator. Therefore a graphical interface is being created that will display

- a reduced "map" of conditional probability of important adjustable variables where the best product quality is expected,
- a projection of the actual working point and
- the advice where to move the working point to maximize the probability of the highest quality.

A very simplified example illustrating basic idea of such graphical interface is shown on fig. 3. The black mark represents the actual working point moving over contour lines of probability density functions during rolling.

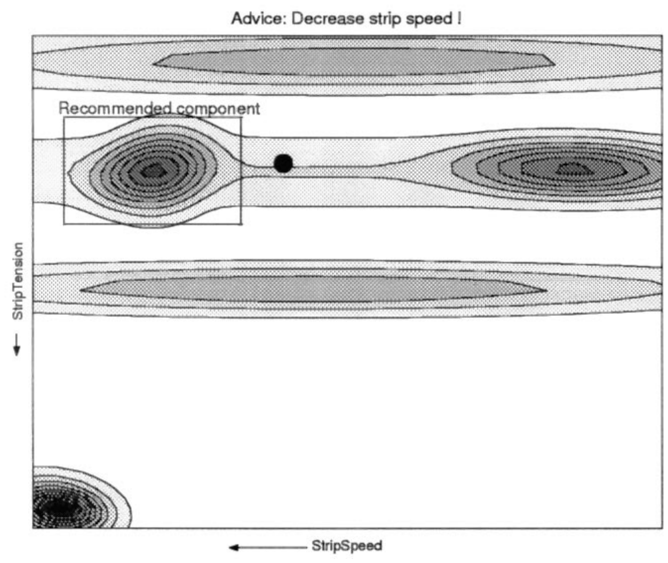

Figure 3: A simplified example of the graphic interface

The displayed probability map allows the operator to see how differs the "probability of good quality" of his working point and the optimal one. The operator then need not to follow the best point in each time if mentioned probabilities are similar. The main problem consists in transformation of multidimensional pdfs into an instructive picture in real-time. First promising attempts have been already made in this respect.

4 Conclusions

The main idea of the project is to extract valuable information from a huge amount of process data. The information should be used for a decision-support tool for process operators to maximize probability of the highest possible quality of the product. The project is in the stage of off-line analysis of process data and experiments with new algorithms on simulated data. The recently finished first phase of the project turned out that the basic idea is realistic but new problems emerged as well. The consortium hopes to lead the project to successful industrial application during its second phase.

5 Acknowledgements

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